경영학 석사학위논문

The Hidden Agenda behind Markets for Technology:

Do firms seek knowledge beyond partners?

2017 년 7 월

서울대학교 대학원

경영학과 경영학 전공

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ABSTRACT

The Hidden Agenda Behind Markets For Technology: Do firms seek knowledge beyond partners?[1]

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In this paper, I aim to better understand why firms enter inter-organizational relationships. Previous studies have shown that firms engage in partnerships to internalize knowledge from its partners. I propose that firms form inter-firm ties to

[1] I am very grateful to my advisor, Professor Jaeyong Song, as well as Professors Dong-Kee Rhee, Theresa Cho, Keun Lee, Yongwook Paik, Joon Mahn Lee, and all seminar participants at Lab 706 for their incredibly thoughtful input. All errors are mine alone.

acquire knowledge from their partner's R&D portfolio as well. Using VentureXpert and SDC Platinum databases, my findings show that Corporate Venture Capitals (CVCs) are more likely to invest in an entrepreneurial firm with an R&D partner over one without. Further, I find that my baseline findings are stronger in industries with weak intellectual property protection (IPP) regimes and when the venture firm's alliance partner operates in a similar industry with the CVC. To resolve endogeneity issues, I provide an additional analysis differentiating investor types. My paper indicates that, under certain contingencies, firms do engage in inter-firm relationships to learn from the partner's R&D portfolio.

Keywords: Innovation, inter-firm relationships, Corporate Venture Capital (CVC), Knowledge Acquisition

***Student Number*:** 2015-20643

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I. INTRODUCTION

“BOE, the biggest display manufacturer in China, has proposed setting up a joint venture in the organic light-emitting diode (OLED) business with partners of LG Display and Samsung Display, sources said Friday.... Analysts and officials; however, say if key Samsung and LG display partners join BOE for a joint venture in OLEDs, then issues over "technology leakage" will emerge as Korea is still ahead of companies in China in the OLED sector.”

– *The Korea Times*, (2015)

[Tsinghua] plans to inject a total of $2.6 billion into the three [companies, ChipMOS, Powertech, and SPIL] in exchange for stakes plus one board seat at each with no management control. The offers came after Micron Technology Inc. rejected Tsinghua's informal $23 billion takeover bid on the presumption of U.S. national security concerns.

– *Reuters* (2015)

The two tech companies in the opening anecdotes have entered inter-organizational relationships seeking to acquire knowledge held by their partner firm’s partner. BOE has established joint ventures with the R&D partners of its largest rivals, Samsung and LG Display. Tsinghua has made equity investments in ChipMOS, a back-end company that assembles more than a billion of Micron's DRAM and NAND chips, shortly after the Chinese tech giant failed to acquire Micron and Micron's technology. This paper investigates firm motivations to enter inter-firm relationships. A central question I ask in this paper is whether firms engage in inter-firm relationships to gain knowledge through second-order ties (i.e., partner's partner) and under what conditions firms do so.

Scholars have long argued that internalizing partner's skills and knowledge is a key motivation for firms to enter inter-firm relationships, such as joint ventures, strategic alliances, equity investments, and technological acquisitions (Ahuja & Katila, 2001; Dushnitsky & Lenox, 2005b; Hamel, 1991; Hamel, Doz, & Prahalad, 1989; Kogut, 1988; Mowery, Oxley, & Silverman, 1996). However, such an explanation is insufficient to explain why tech firms choose to form ties with partner firms that lack apparent benefits. Tech leaders in knowledge intensive industries frequently collaborate with partners that retain inferior skills (Hoang & Rothaermel, 2005) and invest in entrepreneurial firms with nascent technology (Gompers & Lerner, 2000).

This paper proposes a novel explanation of why firms enter inter-firm ties — knowledge acquisition through second-order ties (Ahuja, 2000; Hernandez, Sanders, & Tuschke, 2015). I argue that a key motivation for firms to form ties with other firms is to acquire knowledge of their partner firm's partner. To test my argument, I examine large technology firms' investment decisions in entrepreneurial firms. A burgeoning literature on Corporate Venture Capitals (CVC) has shown that large technology firms use equity investment as a toolkit to learn from entrepreneurial firms (Dushnitsky & Lenox, 2005b; Wadhwa & Kotha, 2006). Using VentureXpert database, I create CVC-venture dyads and find that an entrepreneurial firm is more likely to receive investments when it collaborates in R&D with other firms. I further test heterogeneous effects according to industry-level and firm-level characteristics. First, I examine industry's intellectual property protection (IPP) regimes and show that my main hypothesis is significant in weak IPP regimes (e.g., semiconductor and electronics) but not significant in strong IPP regimes (e.g., biotech and pharmaceutical). Also, I investigate industry similarity between the venture's R&D partner and the CVC to find that CVCs are more likely to invest in a start-up with an alliance partner when the partner operates in a similar industry to the CVC.

Drawing causal inference is challenging in my research setting due to confounding factors. For example, if start-ups with R&D partners have better quality compared to those without, CVCs may invest in a venture with partners because it has superior quality. I attempt to resolve this endogeneity issue by differentiating investor types. Unlike CVCs, independent venture capitals (IVCs) are financial investors that make investments in ventures for financial returns (Garrido & Dushnitsky, 2016). I find that IVC investments are not sensitive to start-ups' alliance portfolio when making equity investments in entrepreneurial firms. The result buttresses my view that CVCs make equity investments in venture firms in order to accumulate knowledge through second-order ties.

My research mainly contributes to the partner selection literature. Studies in this literature stream have long questioned how firms choose partners during inter-firm relationships (Chung, Singh, Lee, & others, 2000; Diestre & Rajagopalan, 2012; Dushnitsky & Shaver, 2009; Li, Eden, Hitt, & Ireland, 2008; Reuer & Lahiri, 2013; Rothaermel & Boeker, 2008). Literature has particularly focused on the dyadic characteristics between two partnering firms to explain this phenomenon. For instance, (Rothaermel & Boeker, 2008)) examine how technological complementariness and similarities between two firms influence the probability of alliance formation in pharmaceutical and biotechnology industries. Reuer and Lahiri (2013) focus on the geographical distance between two firms. However, firm motivation to enter inter-firm ties cannot be fully understood without considering partner's alliance portfolio. The opening anecdotes show how partner firms can be mere conduits of knowledge rather than actual targets during interfirm relationships. My goal is to extend the partner selection literature by underscoring the role of second-order ties in firms' partner selection decision.

This study also adds to the recent empirical studies regarding the "swimming with sharks" dilemma (Dushnitsky & Shaver, 2009; Katila, Rosenberger, & Eisenhardt, 2008; Pahnke, McDonald, Wang, & Hallen, 2015). This stream of literature has shown entrepreneurial firms' strategies to protect themselves against knowledge misappropriation by incumbents. For example, Dushnitsky and Shaver (2009) show that venture firms are less likely to receive CVC investments under a high risk of misappropriation. Pahnke et al., (2015) show that start-ups decrease their innovativeness when exposed to competitors by venture capitals. I complement this literature by focusing on the sharks (i.e., knowledge-seeking firms) and delve into their strategies to overcome entrepreneurial firms' protection strategies. My results suggest that established firms leverage second-order ties to acquire valuable knowledge from other firms, which are reluctant to share their knowledge with competitors.

The rest of the paper is organized as follows. In section 2, I explain my research setting. In section 3, I theorize why CVCs are more likely to invest in ventures that have (more) alliance partners and find contingencies. In section 4, I elaborate my empirical strategy. In section 5 and 6, I provide results and supplement it with an additional analysis. Finally, I conclude by summarizing my key findings in section 7.

II. EMPIRICAL SETTING

My empirical setting focuses on large technology firms' investment decisions in entrepreneurial firms, otherwise known as Corporate Venture Capital (CVC) investments. I examine whether CVC investment likelihood in an entrepreneurial firm is sensitive to the venture's R&D portfolio. This research setting provides several advantages. First, knowledge transfer between CVCs and entrepreneurial firms is unilateral compared to other types of inter-firm relationships including alliances or joint ventures (Dushnitsky & Shaver, 2009; Mowery et al., 1996). The entrepreneurial finance market is a market for technology in which investors buy technology by making financial investments in entrepreneurial firms (Arora, Fosfuri, & Gambardella, 2004). Thus, knowledge flow from CVCs to ventures is limited whereas feasible vice versa. (Dushnitsky & Shaver, 2009). This unilateral knowledge flow prevents potential knowledge *leakage* through second-order ties from CVCs to venture partners, an outflow of knowledge which can deter CVCs from making investments (Pahnke et al., 2015).

Second, literature has not fully understood why CVCs make investments in entrepreneurial firms. Entrepreneurial firms that receive investment often propose an ambiguous value with uncertain technology. I propose that knowledge provided by start-ups' R&D partners play a significant role in those ventures receiving investment. Although I limit my analysis to a specific setting due to several merits, I believe that my findings can be generalized to other types of inter-organizational relationships as well.

III. THEORY AND HYPOTHESES

3.1 Baseline Hypothesis

Entrepreneurial firms gain knowledge during R&D collaborations in two ways. First, the two firms create new knowledge by recombining each other's. Many large-scale empirical studies suggest a positive relationship between strategic alliances and firm innovation performance (Schilling, 2015; Schilling & Phelps, 2007). Newly created knowledge result in new product development or enhance tacit knowledge held by startups' employees (Argote & Ingram, 2000). Second, knowledge flows from incumbents to entrepreneurial firms (Kogut, 1988; Mowery et al., 1996). Knowledge transferred from venture's R&D partners reside in tasks and employees of ventures (Argote & Ingram, 2000).

The newly created (transferred) knowledge with (from) R&D partners becomes marginal benefits to CVCs. CVCs gain opportunities to learn from the venture's technology by making equity investments in ventures

(Dushnitsky & Lenox, 2005b; Gompers & Lerner, 2000; Wadhwa & Kotha, 2006). Learning occurs through various means including maintaining board seats, exchanging liaison teams, conducting due diligence, etc. (for a review see Dushnitsky & Lenox, 2005b). CVCs gain access to new product developments by conducting due-diligence and acquire knowledge embedded in human capital by exchanging liaison teams. CVCs also monitor start-ups to accumulate knowledge in start-ups' tasks. The upshot is that CVCs benefit from knowledge created by (or transferred from) the venture's alliance portfolio by making equity investments start-ups.

A recent real-world example elaborates the theoretical claim made in this paper. In December 2012, Cisco Systems agreed to collaborate in R&D with Streetline, an entrepreneurial firm that develops parking applications for drivers. In May 2014, two years after their partnership, Cisco has successfully combined their IOT technology with Streetline's sensors and developed new parking solutions and IOT gateways which allow Streetline's parking data to be transmitted through Cisco's city Wi-Fi. Interestingly, in January 2013 (a few months after Cisco and Streetline's collaboration), Qualcomm Ventures, participated in Streetline's series C funding. Qualcomm Ventures is a firm that has consistently shown strong interest to diversify into IOT.

I argue that CVCs invest in venture firms in order to acquire knowledge created and transferred from the venture's R&D partners. To test this argument, I first examine whether, all else being equal, CVCs are more likely to invest in ventures *with* alliance partners over ventures *without*. Ideally, such a correlation suggests that CVCs are motivated by the venture's alliance portfolio when making equity investments in start-ups. Thus, my first hypothesis is as follows:

Hypothesis 1: CVCs are more likely to in a startup with an R&D collaboration partner over one without.

3.2 Moderating Hypotheses

In this section, I moderate my baseline hypothesis according to industry-level and partner firm-level variables. The moderators serve two purposes. First, I aim to find contingencies in which second-order ties matter. At the industry level, I focus on industry's intellectual property protection (IPP) regimes. I expect CVCs that operate in weak IPP industries to be more sensitive to start-ups' alliance portfolio when making equity investments. At the partner firm-level, I examine industry similarity between a CVC and a venture's R&D partner. I expect CVCs to invest in an entrepreneurial firm more when the start-up's R&D partner operates in a similar industry to them.

Second, the moderators attempt to resolve endogeneity concerns that arise when ventures with R&D partners have better technology. Under such correlations, an entrepreneurial firm can *signal* higher quality to CVCs by having alliance partners (Spence, 1973). For instance, Qualcomm may have invested in Streetline not because Qualcomm sought to acquire knowledge from Cisco but because such partnership signals high-quality to CVCs. This is an alternative explanation that can drive the same results as Hypothesis 1. Thus, the moderators in this paper provide evidence that the baseline hypothesis is not caused by this alternative explanation but by my proposed mechanism of knowledge seeking through second-order ties.

Intellectual property protection (IPP) regimes

I first moderate my baseline hypothesis using industry IPP regimes. I expect my main hypothesis to be stronger in industries with weak IPP regimes, as knowledge acquisition is easier in such industries. Teece defined IPP regimes as “the environmental factors, excluding firm and market structure, that govern an innovator’s ability to capture the profits generated by an innovation” (Teece, 1986). IPP regimes heavily affect a firm’s ability to defend its knowledge against leakage to other firms. In a strong IPP industry, new products that are developed during R&D collaborations are easily protected by patents or secrecy. Thus, learning from ventures’ alliance portfolio becomes difficult in such industries. I follow the literature and classify semiconductor, electronic components, and electronic equipment industries as weak IPP industries and biotech, pharmaceutical, and chemical industries as strong IPP industries. (Cohen, Nelson, & Walsh, 2000; Dushnitsky & Shaver, 2009). According to the Carnegie Melon Survey (CMS) of inter-industry variation in IPP regimes, these are the top and bottom three industries that score the highest or the lowest in patent protection (Cohen et al., 2000). Hypothesis 2 is as follows:

Hypothesis 2: The positive impact of a startup's R&D partner on CVC investment likelihood (i.e., Hypothesis 1) will be stronger when a CVC operates in a weak IPP industry.

Hypotheses 2 serves to defend against the alternative explanation based on the signaling effect theory. I employ the idea that the direction of Hypothesis 2 would be the opposite (i.e., Hypothesis 1 would be stronger in industries with *strong* IPP regimes) if the baseline hypothesis (Hypothesis 1) is supported due to signaling effects. Literature shows that alliance partners serve as strong quality signals particularly in biotech and pharmaceutical industries. (Nicholson, Danzon, & McCullough, 2002). Thus, having R&D partners will increase investment likelihood more in biotech and pharmaceutical industries (i.e., strong IPP regimes) compared to other industries. The direction of each mechanism is summarized in Table 1. To sum up, if supported, Hypothesis 2 strengthens the claim that my proposed mechanism in Hypothesis 1 is correct.

Table 1 about here

Industry similarity between CVC and alliance partner

Not all second-order ties will attract CVCs, as not all knowledge benefits are equal. In particular, industry similarity between CVCs and venture's alliance partner heavily affects the size of knowledge benefits. The industry similarity between two firms affects their ability to absorb knowledge from each other (Cohen & Levinthal, 1990). Moreover, knowledge of related products and customers are more valuable than that of non-related knowledge (Amit & Schoemaker, 1993; Rothaermel & Boeker, 2008). Recall how BOE has established joint ventures with partner firms of Samsung and LG, two leading firms in the same industry. I hypothesize that industry similarity between CVCs and the R&D partners of start-ups will positively moderate Hypothesis 1.

Hypothesis 3: The positive impact of a startup's R&D partner on CVC investment likelihood (i.e., Hypotheses 1) will be stronger when a CVC operates in a similar industry with the R&D partner of the invested startup.

IV. METHODOLOGY

4.1 Data

I use Thomson Reuters' VentureXpert and SDC Platinum databases as my primary data sources. Using VentureXpert database, I collect information of all *expansion* stage U.S. venture rounds that took place during 2011-2013. I limit my analysis to a single stage (expansion stage) and a short period of time (three years) in order to reduce unnecessary variation among venture rounds. I focus on expansion stage among many investment stages because CVC investment is most frequent during that stage. In addition, I chose my three-year analysis period (2011-2013) in order to give sufficient amount of time for the entrepreneurial finance market to recover after the 2008 financial crisis. From my venture rounds, I identify (1) all CVCs that have made at least one investment in an entrepreneurial firm and (2) all ventures that have received funding from a venture capital during my analysis period. I exclude start-ups founded before 2000 to focus on newly founded entrepreneurial firms (Benson & Ziedonis, 2009). My final sample consists of

1,597 VC-backed U.S. entrepreneurial firms and 67 CVCs.

My unit of analysis is CVC-venture dyads. Studies in the partner selection literature have primarily used dyadic-level analysis (Dushnitsky & Shaver, 2009; Hellmann, Lindsey, & Puri, 2008; Rothaermel & Boeker, 2008). Using 1,597 ventures and 67 CVCs identified above, I create 106,999 (1597 × 67) dyads. Among the 106,999 dyads, I exclude 199 dyads because their CVC-venture relationship has already been materialized before expansion stage (i.e., realized at “Early” or “Seed” stage). Thus, my final sample consists of 106,800 potential CVC-venture dyads. My econometric strategy is to estimate the probability that a CVC-venture dyad relationship will materialize, using logit regression.

4.2 Dependent Variable

Investment

My main dependent variable is a binary variable that denotes the presence (one) or an absence (zero) of an investment dyad. Namely, this variable indicates a value of one if the focal CVC in the dyad participates in the focal start-up’s funding rounds.

4.3 Independent Variables

I use two variables to measure the *presence* and *size* of the venture firm's R&D portfolio.

Alliance (binary variable)

First, I use a dichotomous variable that indicates one if the start-up has established at least one R&D partnership prior to receiving investment at the expansion stage.

Number of alliances (count variable)

Similarly, I use a count variable that measures the total number of alliance partnerships the entrepreneurial firm has established prior to entering expansion stage funding.

4.4 Moderating Variables

IPP Regime (binary)

This variable indicates whether the CVC operates in an industry with strong or weak IPP regime. The Carnegie Melon Survey (CMS) of R&D measures the inter-industry variation in IPP regimes (Cohen et al., 2000). Following the literature, I classify an industry as strong IPP regime if the survey respondents score patent protection as effective and as weak if otherwise (Anand & Khanna, 2000; Shane, 2001). In this paper, as aforementioned, I designate semiconductor, electronic equipment, and electronic component industries as weak IPP industries and biotech, chemical, and pharmaceutical industries as strong IPP industries.

CVC-Alliance Partner Industry Similarity

I use four-digit SIC codes to measure industry similarity which scales from 0 to 1. Specifically, I give this variable a value of 0.25, if the first one-digit of the CVC's SIC code and the alliance partner's SIC code match. I give the value 0.5 if the first two digits match and 0.75 if three-digits match. The variable becomes 1 if the SIC codes are the same for both firms. In cases where the venture firm has more than one alliance partner, I use the maximum value among all partners. This is to account for that fact that CVCs are most likely to benefit from an alliance partner that operates in the most similar industry to them.

4.5 Control Variables

Controlling for venture quality is critical amongst all. I use variables from the partner selection literature and variables of my own to control for venture quality.

Ex-post IPO (binary)

This variable is a binary variable that equals one if the entrepreneurial firm successfully went public after expansion stage funding. Following the literature, I use start-up's success to IPO as a proxy for its quality (Dushnitsky & Shaver, 2009; Gompers & Lerner, 2000).

Log(Amount) ($000)

This variable is the logarithm of the total amount of funding the start-up received prior to expansion stage funding. A venture firm's prior valuations will reflect its overall quality.

Number of investors

This variable is the sum of the total number of investors that have invested in the venture firm before the venture received expansion stage funding. I contend that the number of investors that invested in the start-up is related to venture quality.

Number of rounds

This variable is the number of funding rounds the entrepreneurial firm has received prior to entering expansion stage funding. I exploit this variable to control for heterogeneity among venture funding rounds.

Venture Age

This variable indicates the total number of years passed since start-ups' founding.

California

This is a binary variable that equals one if the venture firm is located in California. I control for this variable as start-ups in California may benefit from knowledge spillover (Audretsch, 1998).

CVC-venture industry similarity

This variable measures the industry similarity between the CVC and the venture. I measure this variable by using SIC codes. The measurement for this variable is exactly the same as the variable *CVC-alliance partner industry similarity,* but here I compare SIC codes of the CVC and the venture firm.

Industry

This is a categorical variable that controls for the industry of the entrepreneurial firm. Using SIC classification, I divide ventures into eight industries: communications; construction; electric, gas, and sanitary; finance; manufacturing; mining; retail; services; software; transportation; wholesale.

Prior CVC investment

This is a binary variable that indicates one if the venture has received investment from a CVC, other than the focal CVC in the dyad. I control for this variable because prior ties to CVCs may increase the likelihood of a venture to receive further CVC investments.

Table 2 summarizes the descriptive statistics of my data. Some stylized facts are worth mentioning. First, the mean value of *investment* is 0.002, which indicates that about 0.2% of the total potential relationships were actually realized. The mean value for *alliance* is 0.093, which means that about 10% of the ventures have at least one alliance experience.

Table 2 about here

V. RESULTS[2]

Table 3 provides analyses for Hypothesis 1. The independent variable in Model 1 is *alliance*, a binary variable that indicates one if the venture has at least one R&D partner prior to entering the funding round of interest (i.e., expansion stage). *Alliance* is significantly positive at the 1% level, supporting Hypothesis 1. The independent variable in Model 2 is *Number of alliances*. This is a count variable that sums the number of R&D partnerships a start-up has made before entering the funding round of interest. The coefficient for *Number of alliances* is not significantly different from zero. This indicates that the total number of alliance partners do not significantly impact investment likelihood, although the presence of second-order ties does. This may be because CVCs target specific R&D partners rather than seek knowledge from the whole portfolio when investing in startups with R&D partners. In such cases, the size of the alliance portfolio would not matter to CVCs.

Table 3 about here

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[2] I use the logit regression model for all regressions in this paper.

Table 4 provides an analysis of Hypothesis 2. The independent variable is again *alliance*. Using the CMS Survey, I divide ventures into two groups: weak IPP and strong IPP (Cohen et al., 2000; Dushnitsky & Shaver, 2009). I classify biotech, pharmaceuticals, and chemicals as industries with strong IPP, and semiconductor, electronic components, and electric equipment as weak IPP. The coefficient of *alliance* is significantly positive in weak IPP industries but not significantly different from zero in strong IPP industries. The results strongly support Hypothesis 2 (Hoetker, 2007).

The results from Table 4 support the fact that my baseline hypothesis is caused by my proposed mechanism. If the results in my baseline hypothesis were caused by alternative explanations such as signaling effects of venture quality, there is no reason for the results to be stronger in weak IPP industries. Rather, the results would be stronger in biotech or pharmaceutical industries as signal effects are stronger in these industries.

Table 4 about here

Table 5 tests Hypothesis 3. In this analysis, I compare venture firms based on their alliance partner's characteristics. Thus, I limit my analysis to start-ups with at least one alliance partner. The independent variable in this analysis is *CVC-Alliance Partner Industry Similarity.* This variable is a 5-scale variable that measures how many first digits of the CVC and the venture's alliance partner match. The results show that *CVC-Alliance Partner Industry Similarity* is positively significant at the 10% level. Therefore, Hypothesis 3 is weakly supported.

Table 5 about here

VI. ADDTIONAL ANALYSIS

Do CVCs invest in ventures with alliance partners to learn from second-order ties or do they simply choose ventures with the best quality? I address this question by conducting a separate analysis that differentiates investor types. IVCs (independent venture capitals) are pure financial investors that seek financial returns through IPO, whereas CVCs are technology firms that aim to learn from entrepreneurial firms by making investments in them (Garrido & Dushnitsky, 2016). The key idea is that venture's R&D partners will affect CVCs and IVCs differently. In other words, knowledge benefits provided by ventures' alliance portfolio will attract CVCs as theorized in Hypothesis, 1 but will not attract IVCs since financial investors have no interest in acquiring external technology.

If my baseline results are caused by signaling effects, on the other hand, venture's R&D partners will have significant effects on both IVC and CVC investment likelihood. Namely, the quality of ventures is important for both types of investors, despite their different motivations to invest in start-ups. CVCs aim to learn from start-ups with the highest quality, and IVCs try to identify ventures with good quality to increase their chance of IPO.

I identify one hundred IVCs that have made the most frequent investments in entrepreneurial firms during 2011-2013 using the VentureXpert database. With these 100 IVCs, I replicate the dyadic analysis conducted in Hypothesis 1. Table 5 provides my results. The results show that I cannot reject the null hypothesis that the effect of venture's alliance portfolio on IVC investment is significantly different from zero. The results support the claim that CVCs chose to invest in a venture with R&D partners, not because alliance partners signal better quality but because CVCs seek to acquire knowledge from second-order ties.

Table 6 about here

VII. CONCLUSION

In this paper, I aim to answer the following question: Do CVCs invest in entrepreneurial firms to acquire knowledge of the start-up's R&D partners? Building on alliance and entrepreneurship literature, I theorize how CVCs can benefit from venture's R&D partners. I build a large dataset from the VentureXpert and SDC Platinum databases to test my hypotheses. My findings from logit regressions suggest that there is a strong correlation between ventures' alliance experience and CVC investment likelihood. I further find contingencies based on industry IPP regimes and industry similarity. Finally, I conduct a separate analysis using IVCs to strengthen casualty. Collectively, my results suggest that CVCs are more likely to invest in ventures with R&D partners because of the knowledge benefits provided by the venture's R&D partners.

My findings contribute to two separate literature streams. First, I contribute to the partner selection literature. No study, as far as I know, has considered second-order ties to be important in a firm's partner selection decision. However, from my point of view, it is difficult to understand real world phenomena without considering second-order ties. I also contribute to the "swimming with sharks" literature. Scholars have mostly focused on firm strategies to protect themselves against sharks (i.e., knowledge seeking firms), leaving sharks' side uncharted. I suggest that firms rely on second-order ties to acquire external knowledge when knowledge acquisition through direct ties is limited. Although my research setting is limited to the entrepreneurial finance market, I believe that my findings can help explain other inter-firm behaviors as well.

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TABLE 1: Direction of Second-order Ties

Impact of Second-order ties on investment likelihood	**Weak IPP**	**Strong IPP**
Knowledge acquisition theory	Strong	Weak (Protected by patents)
Signaling Effect	-	Strong (Strong signals in biotech, pharmaceutical industries)

TABLE 2: Descriptive Statistics

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9
1	Investment	0.002	0.05									
2	Alliance (binary)	0.093	0.29	0.006								
3	Number of alliances	0.342	1.67	0.002	0.465							
4	Ex-post IPO	0.027	0.16	-0.003	0.051	0.077						
5	Log (Amount)	10.128	1.87	0.017	0.08	0.064	0.113					
6	Number of Investors	6.462	3.91	0.032	0.046	0.057	0.081	0.568				
7	Number of Rounds	5.759	3.28	0.012	0.096	0.097	0.055	0.478	0.577			
8	Venture Age	5.106	1.41	-0.007	0.087	0.066	0.05	0.044	0.041	0.22		
9	California	0.439	0.5	0.012	0.043	0.015	0.059	0.205	0.157	0.04	-0.048	
10	CVC-Alliance industry similarity	0.147	0.3	0.017	-0.008	-0.006	-0.008	-0.001	-0.006	-0.03	-0.014	0.01

TABLE 3: Likelihood of CVC Investments

DV: Investment	Model 1	Model 2
(Intercept)	-20.10 (1313.29)	-20.186 (1313.29)
Alliance Portfolio	**0.41** (0.17)**	
Number of alliances		**0.037 (0.03)**
ln (Amount)	0.06 (0.05)	0.061 (0.05)
Ex-post IPO	-0.71* (0.42)	-0.738* (0.42)
Number of Investors	0.13*** (0.02)	0.127*** (0.02)
Number of Rounds	-0.05* (0.02)	-0.043* (0.02)
Venture Age	-0.06 (0.04)	-0.050 (0.04)
California	0.21* (0.12)	0.213* (0.12)
Industry: Communications	12.54 (1313.29)	12.556 (1313.29)
Industry: Construction	12.88 (1313.29)	12.931 (1313.29)
Industry: Electric, Gas, Sanitary	-0.69 (1354.36)	-0.615 (1354.5)
Industry: Finance	12.57 (1313.29)	12.600 (1313.29)
Industry: Manufacturing	13.37 (1313.29)	13.395 (1313.29)
Industry: Mining	-0.54 (1417.91)	-0.542 (1417.88)
Industry: Retail	13.20 (1313.29)	13.273 (1313.29)
Industry: Services	12.89 (1313.29)	12.932 (1313.29)
Industry: Software	13.14 (1313.29)	13.179 (1313.29)
Industry: Transportation	12.80 (1313.29)	12.838 (1313.29)
Industry: Wholesale	-0.01 (1374.08)	-0.006 (1374.07)
CVC-Venture industry similarity	0.842*** (0.16)	0.842*** (0.16)
CVC Prior investment	-1.858*** (0.39)	-1.869*** (0.39)
Observations	106,999	

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

TABLE 4: Industry IPP Regimes

Dependent Variable: Investment	Weak IPR	Strong IPR
Alliances	**1.34*** (0.64)**	**1.04 (0.85)**
ln(Amount)	0.17 (0.4)	0.02 (0.21)
Number of Investors	0.52*** (0.19)	0.26*** (0.1)
Number of Rounds	-0.44*** (0.14)	-0.15 (0.11)
Venture Age	-0.08 (0.3)	0.41* (0.23)
California	0.75 (0.87)	-0.19 (0.56)
Expost IPO	-14.17 (35550.48)	-0.89 (0.56)
CVC-venture industry similarity	1.72*** (0.63)	3.69*** (0.68)
CVC Prior investment	-16.38 (911.99)	0.19 (0.79)
(Intercept)	-10.86*** (4.69)	-10.36*** (2.5)
Industry	Semiconductor, Electronics	Bio, Pharmaceuticals, Chemical
Observations	5,076	8,966

*p<0.1; **<0.05; ***p<0.01

TABLE 5: Industry Similarity

Dependent Variable: Investment	
CVC-Alliance Partner Industry Similarity	**1.37*** **(0.06)**
ln(Amount)	0.14 (0.16)
Number of Investors	0.13*** (0.15)
Number of Rounds	-0.12* (0.07)
Venture Age	-0.16 (0.22)
California	0.16 (0.65)
Ex-post IPO	-15.73 (1215.3)
CVC-venture industry similarity	0.94*** (0.44)
CVC Prior investment	-1.92*** (0.44)
(Intercept)	-23.12 (1246.1)
Industry factor variables	Controlled (NOT significant)
Observations	10,023

*p<0.1; **<0.05; ***p<0.01

Table 6: Likelihood of IVC Investment

Dependent Variable: Investment	
Alliance	0.07 (0.08)
ln(Amount)	0.31*** (0.03)
Number of Investors	0.01 (0.01)
Number of Rounds	-0.03** (0.01)
Venture Age	-0.03* (0.02)
California	0.26*** (0.05)
Ex-post IPO	0.13 (0.12)
CVC Prior investment	0.42*** (0.06)
Intercept	-17.33 (88.28)
Industry factor variables	Controlled
Observations	128,281

*p<0.1; **<0.05; ***p<0.01

요약(국문초록)

위 논문은 기업형 벤처캐피털이 왜 벤처기업에 투자하는지 연구한다. 그 동안의 연구들은 기업형 벤처캐피털의 주요 투자목적이 벤처기업으로부터의 지식습득에 있다고 말해왔다. 본 연구는 기업형 벤처캐피털의 투자목적이 단순히 벤처기업의 지식습득에 있는 것이 아니라, 벤처의 연구개발 파트너로부터의 지식습득에도 있음을 주장한다. 본 연구는 벤처엑스퍼트 및 SDC 플래티넘 데이터베이스를 활용하여, 벤처기업이 연구개발 파트너가 있을 경우 (파트너가 없을 경우보다) 기업형 벤처캐피털로부터 투자 받을 확률이 유의하게 높아짐을 보인다. 또한 특정 산업의 특허를 통한 지적재산권 보호강도와 벤처캐피털과 벤처의 연구개발 파트너간의 산업 유사도를 통한 조절효과를 분석하여 인과관계를 추론한다.

주요어 : 혁신, 기업간 상호관계, 기업형 벤처캐피털, 지식습득

학 번 : 2015-20643